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Reactive Power Optimization with Chaotic Firefly Algorithm and Particle Swarm Optimization in A Distribution Subsystem Network

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Abstract: *In this paper the minimization of power losses in a real distribution network have been described by solving reactive power optimization problem. The optimization has been performed and tested on Konya Eregli Distribution Network in Turkey, a section of Turkish electric distribution network managed by MEDAŞ (Meram Electricity Distribution Corporation). The network contains about 9 feeders, 1323 buses (including 0.4 kV, 15.8 kV and 31.5 kV buses) and 1311 transformers. This paper prefers a new Chaotic Firefly Algorithm (CFA) and Particle Swarm Optimization (PSO) for the power loss minimization in a real distribution network. The reactive power optimization problem is concluded with minimum active power losses by the optimal value of reactive power. The formulation contains detailed constraints including voltage limits and capacitor boundary. The simulation has been carried out with real data and results have been compared with Simulated Annealing (SA), standard Genetic Algorithm (SGA) and standard Firefly Algorithm (FA). The proposed method has been found the better results than the other algorithms.*

Keywords: Chaotic firefly algorithm, distribution subsystem network, particle swarm optimization, power loss, reactive power optimization.

I. INTRODUCTION

The increasing demand in power systems affects power losses, power quality and the economic operation of the systems. In power systems, the reactive power optimization (RPO) can efficiently decrease the total active power losses of the energy systems and improve the voltage level, which has an impress on economical management of power system [1-7]. RPO denotes that all these reactive setting methods, which can be found through the optimization of some specific variables when structure parameters and load situation of system are given, and under the premise that when all specified constraint conditions are satisfied, which can fix one or more performance indexes of system to approach the optimization [8]. In the past, many conventional techniques such as dynamic programming [9], linear programming [10] and interior point methods [11] have been used to solve the reactive power optimization problem.

The heuristic searching and optimizing algorithm, such as tabu search (TS), has also been proposed in [12]. In paper [13] the evaluation of different GA selection, the crossover and mutation techniques in term of convergence to the optimal solution for single objective reactive power optimization problem has been investigated. Iba [14] used genetic algorithm with the interbreeding between populations to solve power system reactive power optimization problem. Lee [15] proposed an improved genetic algorithm that combined with successive linear programming to solve the reactive power optimization problem. Nara et al. [16] offered a solution using a genetic algorithm (GA) to search the minimum loss configuration in the distribution system. The genetic algorithms are widely used for the purpose of load modeling parameter estimation, as shown in [17], where its results have been compared to Levenberg-Marquardt method. Zhang and Liu [18] proposed particle swarm optimization and they implemented proposed approach to a practical power system. The application of PSO in the reactive power optimization has been carried out in an IEEE-6 bus system [19]. In paper [20], a fuzzy adaptive particle swarm optimization algorithm has been proposed to solve a reactive power optimization problem.

Wang et al. [21] proposed a chaos particle swarm optimization. In paper [22], an improved particle swarm optimization algorithm based on multi-agent technology has been proposed to solve a reactive power optimization problem. The authors [23] proposed hybrid ant colony and ant colony which are used for reactive power optimization. Wei et al. [24] computed power loss with Bacterial Chemotaxis Method in different power systems. Li et al. [25] proposed a tabu search to minimize the power loss. Rao et al. [26] used a Harmony Search Algorithm (HSA) to analyze the network reconfiguration problem to get optimal switching combinations simultaneously in the network to decrease the real power losses in the distribution network.

In this paper, a RPO method has been presented in order to reduce the power loss of Konya Eregli Distribution Network in Turkey managed by *MEDAŞ*. CFA has been preferred to compute the optimal reactive power and to enhance the voltage profile, which reduces power losses of system by regulating the variables. Finally, the results have been compared and it has been found that the analysis is successfully implemented in a real distribution network.

In this study, sections have been listed as follows; in section 2 and 3, proposed methods are explained. In section 4, the problem of reactive power optimization is given and the implementations of algorithms are applying to the problem. Section 5, the results of algorithms is computed and given to compare. In section 6, conclusions of the study are given.

II. FIREFLY ALGORITHM (FA)

In 2008, Dr. Xin-She Yang developed Firefly Algorithm [27], based on swarm intelligence, inspired by behavior of fireflies.

The FA contains three rules; in the first rule, all firefly are unisex therefore they will be more attractive and brighter, in the second rule, the attraction depends on their brightness, this is reduced by the distance between two individuals and if there is one firefly, it will flight randomly, in the last rule, the intensity of the light is defined by the objective function [28].

The variation of light intensity and the formulation of attractiveness are important for FA. The light intensity of a firefly representing the solution $I(s)$ is proportional to the fitness function $I(s) \propto f(s)$. The light intensity of one individual $I(r)$ changing given in the following equation:

$$I(r) = I_0 e^{-\gamma r^2} \tag{1}$$

where r is the distance between two fireflies, I_0 is the intensity of source, γ is the absorption coefficient. The attractiveness of fireflies is similar to the light intensity can be expressed as in the equation below.

$$\beta = \beta_0 e^{-\gamma r^2} \tag{2}$$

where β_0 is the attractiveness at r=0. While the intensity is referred to as an absolute measure of emitted light by the firefly, the attractiveness is a relative measure of the light that should be seen in the eyes of to be holders and judged by other fireflies [29]. The distance between fireflies i and j defined as:

$$r_{ij} = \|x_i - x_j\| \tag{3}$$

The movement of a firefly i is attracted to another more attractive firefly j illustrated in [30] is given as;

$$x_i^{k+1} = x_i^k + \beta_0 e^{-\gamma r_{ij}^2}\left(x_i^k - x_j^k\right) + \alpha^k\left(R - \frac{1}{2}\right) \tag{4}$$

where α is the randomization parameter and R is the random number between 0 and 1 which generated uniformly. If $\beta_0 = 0$, firefly moves randomly. The speed of convergence and the algorithm behaviors are affected by γ, it is shown as $\gamma \in [0, \infty)$. But typically, it varies from 0.1 to 10.

A. Chaotic Firefly Algorithm

Chaos is a deterministic system, very sensitive to the initial conditions and parameters. In the nature of chaos, although randomness and unpredictability it has an order. The chaos theory has been applied with success in various heuristic methods [31,32].

In this study, the chaos is applied to best individuals in each iteration. The movement of firefly in k-th iteration obtained by previous individuals is calculated in Equation (7). This procedure continues until it reaches the number of chaotic firefly. The fitness value obtained by chaos is calculated to add into population of fireflies.

Well-known equations that characterize the chaos system, is shown in the following equation;

$$x_{n+1} = 4x_n(1 - x_n) \tag{5}$$

III. Particle Swarm Optimization (PSO)

The PSO algorithm method, has been asserted by Kennedy and Eberhart [33], is originated by the movements of social behavior of organisms such as bird immigrating and fish edifying.

PSO operation is simple. PSO needs the some parameters and the specification of the problem. It is effective in solving many global optimization problems. Occasionally it does not endure the difficulties encountered by the other method. In PSO, a randomized velocity is assigned for each potential solution. Then, this is flown to the hyperspace of the problem. The PSO technique finds the optimal solution using a population of particles. Each particle, gives a potential solution for the main problem, and is acted as a part in an n-dimensional space and has its position defined by $x_i^k = (x_{i1}^k, x_{i2}^k, \ldots, x_{in}^k)$ and a velocity defined by $v_i^k = (v_{i1}^k, v_{i2}^k, \ldots, v_{in}^k)$) in variable space [34,35]. If a particle has the best position, the position of this particle is enrolled to the next position and given as $pbest$, $pbest_i = (p_{i1}, p_{i2,}, \ldots, p_{id})$. The best position of all particles is represented as $gbest$, $gbest_i = (g_{i1}, g_{i2,}, \ldots, g_{id})$.

The velocity and position of each particle in the k-th iteration of the swarm can be expressed in equations. (1) and (2) [36];

$$v_i^{k+1} = w_i v_i^k + c1r1(pbest_i - x_i^k) + c2r2(gbest_i - x_i^k) \tag{6}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{7}$$

where, v is the current velocity, w is the weight function, $r1$ and $r2$ are two random functions in the range [0,1], $c1$ and $c2$ are the acceleration coefficients and set as $c1 = c2 = 2$, $pbest$ is the best position of agent i, $gbest$ is the global best of the group and x is the current position.

The weight function w is;

$$w_i = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{8}$$

The number of particles affects the results of PSO in the swarm N and the algorithm will be caused to become boundary in a local minimum by the small number of particles, on the other side many particles will slow down the algorithm.

IV. Problem Formulation

The objective function given in [4], [5], [7] for the reactive power optimization is shown in the Equation (9). The active power loss of the power system is minimized which is represented as the objective function. The control variables can be composed of the bus voltages, transformer tap positions and switchable shunt capacitor banks. The equality and inequality constraints are denoted in equations between (11) and (14) as active power equality and reactive power equality, respectively. The inequality constraints can contain voltage magnitude values of busses, reactive power values of the busses, values of the capacitors and etc.

$$\min f = \min P_{Loss} \tag{9}$$

where;

$$P_{Loss} = \sum_{i=1}^{N_i} [g_{h(i,j)}.\left(V_i{}^2 + V_j{}^2 - 2.V_i.V_j.\cos(\theta_{i,j})\right)] \tag{10}$$

The constraints equations are given as:

$$P_i - P_{loadi} - V_i.\sum_{j=1}^{n} [V_j.\left(g_{h(i,j)}.\cos(\theta_{(i,j)}) + b_{h(i,j)}.\sin(\theta_{(i,j)})\right)] = 0 \tag{11}$$

$$Q_i - Q_{loadi} - V_i.\sum_{j=1}^{n} [V_j.\left(g_{h(i,j)}.\sin(\theta_{(i,j)}) - b_{h(i,j)}.\cos(\theta_{(i,j)})\right)] = 0 \tag{12}$$

$$T_{imin} \le T_i \le T_{imax} \tag{13}$$

$$Qc_{imin} \le Qc_i \le Qc_{imax} \tag{14}$$

$$V_{imin} \le V_i \le V_{imax} \tag{15}$$

where, N is the number of nodes, P and Q are the active power and the reactive power of generator i, P_{loss} is defined the power loss of all line, P_{load} is the active power of load, Q_{load} is the reactive power of load, respectively. The shunt capacitor value denoted as Q_C, V is the voltage magnitude of node, g and b are the conductance between and the admittance between node i and j, respectively, θ is the angle difference between nodes, T is tap position of transformers.

If there are no considering generators in distribution subsystem, generator active and reactive power outputs are not inserted in the objective function [25]. Because of this, in this study, we considered the constraint equations as (13) and (14). Therefore, the controlling variables can be defined as $[Qc\ V\ T]^t$. Minimum and maximum values of inequality constraints are given in Table I.

Note that, the penalty terms (pt), which are given below, reflect the out-of-limit degree of controlling parameters and add the out-of-limit cost to the object function. Thus, the objective function keeps minimum values within the certain limits.

$$pt = w_1.\sum(\Delta Qc_i)^2 + w_2.\sum(\Delta V_i)^2 + w_3.\sum(\Delta T_i)^2 + \frac{1}{M_i} \quad (16)$$

where w_1, w_2 and w_3, which are set as $w_1 = w_2 = w_3 = 1$, are the penalty weights, M_i is the reactive margin of bus i. By this function, the objective function can be described as in the following:

$$\min f = P_{Loss} + pt \quad (17)$$

A. Implementation

1) Proposed CFA

The flow of CFA algorithm can be given as;
Step 1: Set the objective function
Step 2: Create the population of firefly (create with $random$ function of software)
Step 3: Set the parameters; $\gamma = 1$, $\alpha = 0.2$
Step 4: Start iterations;
Step 5: While $\left(\left|\left|\mathrm{x(k+1) - x(k)} > \mathrm{tolerance}\right|\right| \mathrm{or\ k} < \mathrm{maximum\ number\ of\ iterations}\right)$
$iter = iter + 1$,
Step 6: Find the distance between two individuals by the Equation (3)
Step 7: Calculate the attractiveness by the Equation (5) at $\beta_0 = 1$
Step 8: Ranking fireflies by their light intensity/objectives
Step 9: Find the current best and implement into chaos system with Equation (5)
If $x(i)$ brighter then $x(j)$ then
Select $x(i)$ and implement into chaos step
Step 10: Move to the better locations (Equation (4))
Step 11: Updating fireflies and evaluate the objective function
Step 12: If $\left(\left|\left|\mathrm{x(k+1) - x(k)} \leq \mathrm{tolerance}\right|\right| \mathrm{or\ k} = \mathrm{maximum\ number\ of\ iterations}\right)$ are provided, stop,
Else go to step 5.

In this section, we implemented the chaotic structure to FA algorithm, and then we considered the CFA to compute the objective function in reactive power optimization method. The objective function $f(x)$ is modified, then the initial population of fireflies is initialized by Step 2, then population size is set as $N = 20$ (same as other methods). Then light intensity I is determined and if $I(i) > I(j)$, vary attractiveness with distance and move firefly j towards i. In Step 11, $x_0 \leftarrow x_1$, $I_0 \leftarrow I_1$, and best solution equals to x_0 and best objective value equals to I_0 (fireflies and their intensity have been varied as x_i and I_i in Step 8 previously, where $i = 1, 2, 3, \dots N$). The objective function is evaluated and the algorithm keeps the best value and total number of iterations, display ($fbest\ numiter$). The procedure is continued to do steps 5-12 by the algorithm.

If algorithm is provided stopping criteria ($\mathrm{tolerance} = 1\mathrm{e} - 6$ or $\mathrm{maximum\ number\ of\ iterations} = 100$), then the procedure will be ended.

2) Proposed PSO Algorithm

The flow of the proposed PSO algorithm can be given as;
Step 1: set the objective function
Step 2: create the initial population of swarm with $rand$ function
Step 3: Initialize locations and velocity of particles and evaluate the initial value of objective function
Step 4: set the parameters; $c_1 = c_2 = 2$, $r_1, r_2 = rand[0,1]$, then find the initial local best and global best
Step 5: Start iterations;

Step 6: While $(||x(k+1) - x(k) > \text{tolerance}||$ or $k <$ maximum number of iterations$)$
$iter = iter + 1$,
Step 7: Calculate the new velocity and position of each particle of swarm by equations (6) and (7), and accelerate particles
Step 8: Find current best position
Step 9: Find the global best
Step 10: Updating the weights via Equation (8)
Step 11: If $(||x(k+1) - x(k) \leq \text{tolerance}||$ or $k =$ maximum number of iterations$)$ are provided, stop,
Else go to step 6.

The parameters of this problem are assigned to particles of swarm. The subsequent procedure, initial population of swarm is initialized by step 2 in section 2.1, $N = 20$ (create with $random$ function). The following step is to determine the initial velocity and position and the objective function evaluated for each population and then particles have been accelerated with a acceleration. Local and global best position and minimum value of objective function are indexed. The procedure is continued to do steps 5-10 by the algorithm while $||x(k+1) - x(k) > \text{tolerance}||$ or $k <$ maximum number of iterations. The objective function is evaluated in each iteration (evaluate with $feval$ function), and minimum value of this evaluation is indexed. In Step 8 and Step 9, the procedure updates current best and global best, respectively, (if $f(x_i(iter+1)) < f(pbest_i(iter))$, then do $pbest_i(iter+1) = x_i(iter+1)$ and if $pbest < fbest$, then $gbest = pbest$).

If algorithm is provided stopping criteria ($\text{tolerance} = 1e-6$ or $\text{maximum number of iterations} = 100$), then the procedure will be ended.

V. Case Study and Results

In this study, the subsystem considered in [4], which is Konya Eregli Distribution Network in Turkey managed by MEDAŞ (Electricity Distribution Corporation), is handled to minimize the real power loss. This subsystem contains 1311 0.4kV buses, 9 31.5kV buses and 3 15.8kV buses. The network is fed by including with capacity of 50MVA and 100MVA two transformer stations. The study has been carried out on 1311 buses at 0.4kV voltage level and with constant load. Moreover, all buses voltage capacitor values and transformers tap positions are considered for proposed algorithms.

In this power system, the active power loss measured as 2.610MW in the year 2013. The study in [4], the active power loss has been reduced to 0.924MW with controlling all capacitor banks connected to 0.4kV buses and transformers.

Table I

Upper and Lower Bound of Inequality Constraints

Parameters	min value	max value
$Qc\ (pu)$	0.040	0.700
$V\ (pu)$	0.94	1.06
$T\ (pu)$	0.9	1.1

The algorithms have been developed in MATLAB environment to calculate the optimization problem and also to achieve the required objective function. Algorithms have been performed on Core i7, 1.73GHz PC. Results have been obtained in same conditions such as in all methods population size selected as $N = 20$, number of iteration is set to 100. Comparison results can be shown in Table II. Here, we also used the algorithms to decide the level of bus voltages and the values of capacitor banks for distribution network. All of these algorithms have been run 10 times and to get the solution the last obtained results are shown below.

Table II

Comparison Results of Real Power Loss of The Distribution Network

Parameters	CFA	FA	PSO	SGA	SA
P_{loss} (MW)	0.9067	0.9085	0.9159	0.9208	0.9364

In Table 2, SA, SGA, PSO and FA reduced the power loss as 0.9364MW, 0.9208MW, 0.9159MW and 0.9085MW, respectively. On the other side CFA got the power loss as 0.9067MW. It can be shown that CFA found the better result than other algorithms. The optimization process of all algorithms are shown in Fig. 1. The Fig. 1 points out that CFA found the better result than all of the other algorithms under 20 iterations. Both algorithms got different values for each capacitor banks and bus voltages (i.e. in bus 218, CFA found the capacitor value as $0.044pu$ and PSO found the capacitor value as $0.040pu$, and CFA found the voltage as $0.9925pu$ and PSO found the voltage as $1.0029pu$). The convergence of all methods are shown on Table III. Here, it can be shown that the convergence of CFA takes a long time then other three algorithms, standard FA, PSO and SA for reactive power optimization problem given in this paper.

The numerical analysis with CFA with the energy cost of year 2014 can be decreased the annual management cost of whole network as 6337021.27$ and with FA, PSO, SGA and SA as 6324465.81$, 6273367.38$, 6239983.91$ and 6136028.61$, respectively.

TABLE III

THE CONVERGENCE TIMES

Method	Best Time (s)	Average Time (s)
SA	54	56
SGA	235	251
PSO	126	137
FA	138	152
CFA	198	225

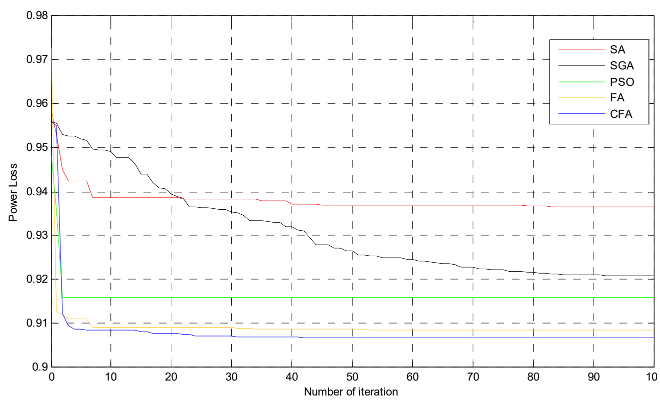

Fig. 1 Changing of power loss in 100 iterations with CFA, FA, PSO, SGA and SA (P_{loss} given as MW).

VI. CONCLUSION

A reactive power optimization problem solving with different algorithms for reducing the power loss in a real distribution subsystem network with real data has been presented in this paper. In the preferred approach, switching capacitors, the optimal values of capacitor banks and voltage level required for each transformer, and setting values of voltage level of transformers are specified. The approach facilitates the model of control variables and satisfies the constraints with constant load. Thus, the algorithms for traditional reactive power optimization can be applied to solve this model directly.

In this paper, CFA and PSO with accelerated individual algorithms are implemented to reactive power optimization problem. The values of all voltages and capacitors of 0.4kV buses is determined by proposed methods. The numerical results show that CFA found the better solution then other methods. The minimum real power loss of the system is found as 0.9067MW by CFA. The results of numerical analysis denote that these algorithms can not only reduce power loss but also provide the economic gains.

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